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SOCIAL MEDIA ANALYSIS OF THE PUBLIC PERCEPTION OF URBAN VEHICLE ACCESS REGULATIONS

Summary. Heavy motorisation in the wake of increasing urbanisation is one of the significant transport problems cities face today. There are practical measures under the panoply of urban vehicle access regulations (UVARs) used to stimulate sustainable mobility behaviour changes in the urban population and reduce reliance on passenger car travel. However, the adoption and implementation of such measures are often riddled with challenges, particularly building public acceptability and preserving social justice. Overcoming these challenges will also require cities to understand how the mobility needs of residents change over time. Considering the limitations of conventional data-collection and monitoring approaches, this study explored and analysed the public perception of UVARs over 12 years through natural language processing techniques using social media as a data source. The results show that UVARs are a prominent topic in public discussion and that the average sentiment expressed in tweets tended to be more positive than negative, with a gradual increase observed over the 12-year study period. In addition, the patterns observed in the data and the topics modelled were consistent with the events and talking points in society related to UVARs. Hence, this study demonstrates that social media data can help policymakers assess public sentiments during the ideation, design, implementation, and operational phases of UVARs and other transport policy measures.

1. INTRODUCTION

Rapid urbanisation and increased mobility demands for urban transport are key challenges in modern society. Despite its many benefits and advantages to humans, transportation, particularly road transport, has been a source of constant worry and concern for governments and policymakers worldwide due to negative externalities. Air pollution, noise, congestion, and accidents, amongst other negative externalities, threaten sustainability. Drastic measures must be taken to curtail the multiple negative trends associated with increased mobility. Therefore, many cities are constantly developing solutions to mitigate mobility's social costs through different urban mobility management approaches [1].

Mitigating these social costs will require the root cause – the extensive dependence of society on passenger cars to meet their personal needs – to be addressed and action to be taken for clean air, additional space for walking and cycling, and the improvement of public transport services. Urban vehicle access regulations (UVARs), which regulate vehicular access to cities, constitute an essential tool in this regard [2]. It employs road pricing, establishing low emission zones, limited traffic zones, lorry bans, pedestrianised areas, car-free days, odd-even schemes, and other spatial interventions.

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UVARs, as push measures, address several challenges that markets and other pull measures alone cannot address effectively [3]. The regulations have succeeded in inducing a sustainable behavioural change in road users, thereby reducing emissions, congestion, and accidents while generating a modal shift towards public transport and active mobility, although at varying levels. Nonetheless, their adoption and implementation do not come without challenges, as limiting access to an area of a municipality for specific vehicles or users can confuse citizens and give rise to criticisms from business owners. Therefore, regulating the entry of cars into urban areas has been a politically controversial instrument of mobility management, with the public acceptability of a proposed UVAR playing a significant role in determining whether or not the proposed UVAR survives the policy process [3–5]. Understanding the mobility needs across all transport users and the probable impacts of UVARs on this diverse group is vital for building and sustaining the public acceptability of the measures. Each UVAR affects many stakeholders and requires specific stakeholders to be involved in decision-making. This is important, as every UVAR will imply a change specific to each individual or stakeholder. However, due to the varying socio-economic situations of residents and mobility users, these impacts tend to change over time. Consequently, public acceptance and opposition often fluctuate over time, meaning acceptance is a continuous process and not a final decision for or against a specific UVAR. Hence, it is imperative to monitor public perception and opinions regularly [6].

The process of monitoring the policy mood based on the preferences and opinions of citizens is quite complex, especially given the dynamic nature of transport. Though they have many advantages, conventional data collection approaches (e.g. voting and questionnaire-based survey methods) also present some limitations. Declining coverage and response rates make these processes tedious and expensive. In addition, they can only offer a snapshot of public perception at fixed and relatively broad intervals, which does not entirely suit the transport policy process [7]. Nevertheless, even if it is practical, someday, due to technological advancement, installing sensors and detectors across every point of transport infrastructure and on every mobility user without overstepping financial and privacy boundaries is not feasible.

The advent and increasing popularity of social media networks and platforms have provided an opportunity to foster government transparency and strengthen the interaction between citizens and public administrations [7]. Social media offers a way for users to express their perspectives and experiences on different issues. The wide availability of this user-generated content allows the application of sentiment analysis techniques to collate and analyse opinions and trends for multiple use cases, including transport cases [8]. In recent times, social media data analysis has been used by researchers to predict daily traffic [9], detect spatiotemporal traffic events [10], identify attributes of public transport services for urban tourists [11], evaluate new mobility offers [12], and even detect traffic accidents [13, 14] While different platforms have been considered across these studies, Twitter, a microblogging platform, has been extensively used due to its high popularity with users through short messages known as tweets and is quite famous with respect to opinions on government issues. Therefore, it provides an effective way to understand people's feelings and viewpoints in relation to major stories from a worldwide perspective.

Owing to the importance of monitoring public perceptions of the implementation and sustenance of UVARs, this study aims to harness the potential of social media to measure public opinion. It explores the general discussion on UVARs to identify the issues, relevant topics, and the ways in which public perception of UVARs has morphed over time. Using the social media platform Twitter, we sampled public opinions on UVARs by retrieving tweets related to different UVAR measures for 12 years without setting geographical boundaries. The overall goal of the work is to study public views on the role, performance, and effectiveness of UVARs as measures to build a sustainable society with reduced dependence on passenger cars through social media data.

2. METHODS

2.1. Data Collection

The data used in this study were collected through the Twitter application programming interface (API) through the Academic Research Product Track. The API offers access to the entire archive of tweets published on Twitter since the social network platform's launch in July 2006, with a monthly retrieval cap of 10 million tweets and a rate limit of 450 requests every 15 minutes [15]. We retrieved UVAR-related tweets posted from January 1, 2010, to May 1, 2022, using the academictwitteR package on R, which provides dedicated functions to query the API endpoints [16]. The starting date was 2010, as this year marked the period Twitter started witnessing a large volume of tweets (estimated at 50 million tweets daily) and almost 75 million visitors daily [17]. The following terms were used in our search query with the spaces in between the terms equivalent to the OR logical condition: "ulez traffic", "car restriction", "emission zone", "clean air zone", "pedestrian zone", "congestion charge", "congestion charging", "car ban", "LEZ traffic car", "limited traffic zone", "urban road toll", "road pricing", "road user charge", "odd-even rule", and "odd-even scheme". Our need to focus on original ideas expressed by the public through Twitter made us limit the search to exclude retweets and tweets containing links (as these were often media reports and announcements). We acknowledge that setting this constraint might have filtered out some tweets which the public could have made, but it was necessary to reduce the preprocessing that would have otherwise been required for the dataset.

2.2. Data Preprocessing

This phase included reducing the noise such as user mentions (@usernames), whitespaces, hashtags, stop words, and slang as much as possible from the Twitter data. Removing such elements to obtain data that can easily be parsed and classified during sentiment analysis is necessary. Non-English tweets were also filtered out at this phase. As the data classification approach used in the study can handle tokens at a sentence level, other common steps commonly involved in the preprocessing phase were taken only after the data classification phase. These steps include converting upper to lower cases, removing punctuation marks, and stemming words to their root forms.

2.3. Data Classification

Data classification through sentiment analysis was undertaken using the lexicon-based valence aware dictionary and sentiment reasoner (VADER) package in R. The VADER dictionary was developed using a combination of methods and attuned to sentiment in microblog contexts like Twitter. Like all natural language processing dictionaries, each unique word in the VADER dictionary has been mapped to an index score [18]. In addition, it combines its lexical features with five heuristics, which incorporate word-order sensitive relationships between terms, including punctuation, capitalisation, degree modifiers, contrastive conjunctions, and tri-gram identification. These heuristics imply that VADER, for instance, adds or subtracts (depending on whether a word is positive or negative) extra empirically obtained scores for words in upper case, words preceded by modifiers, and words followed by exclamations. This creates a possibility for a word appearing within a body of text to be assigned different scores based on its case or the words and punctuation marks that precede or succeed it. The VADER results contain the valence score for each word; an overall compound valence score for the text; the weighted percentages of positive, negative, and neutral words in the text; and the frequency of the word "but" [19]. The compound valence score, adopted as the sentiment score, is the sum of the word score of each sentiment-bearing word normalised to a total value between -1 and +1. It is calculated as follows:

$$\frac{x}{\sqrt{x^2+\propto}} \quad , \tag{1}$$

where x is the sum of the word scores; $\propto$ is a normalisation parameter (set to 15 in the algorithm).

Based on the normalisation approach, as x increases, the value of the sentiment score tends closer to -1 or 1. Therefore, text with more sentiment-scoring words tends to have sentiment scores closer to the poles. Hence, VADER is optimal for short corpora of words like tweets and sentences.

Based on these scores, tweets are classified as negative (sentiment score $\leq$ -0.5), neutral (-0.5 < sentiment score < 0.5), and positive (sentiment score $\geq$ 0.5).

2.4. Topic Modelling

The topic modelling technique adopted in this study is latent dirichlet allocation (LDA). LDA is a widely used unsupervised clustering technique of topic modelling that represents documents as random mixtures of latent topics, by which each topic is characterised by a probability distribution over words. It assumes that each document can be described as a probabilistic distribution over latent topics and that topic distribution in all documents shares a common Dirichlet prior. LDA parameters are often estimated using expectation-maximisation (EM), variational Bayes inference, and Gibbs sampling [20].

EM is an iterative algorithm used to find maximum likelihood estimates of parameters in the presence of unobserved latent variables. The EM algorithm first computes the expectation of the likelihood function with respect to the latent variable given the observed data. Then it updates the parameters to maximise this expected likelihood. The variational Bayes inference is an extension of the EM algorithm that uses a parametric approximation to the posterior distribution of parameters and latent variables. Gibbs sampling is a Markov chain Monte Carlo algorithm for obtaining a sequence of samples from a multivariate distribution. The algorithm can be applied to LDA by alternatingly sampling latent topic assignments and word-topic assignments.

For clustering, the tweets were tokenised into words, and the LDA grouped the data with similarities in the same cluster [21] using the Gibbs sampling technique. Gibbs sampling was used due to its ability to handle complex data and its suitability for text data.

3. RESULTS

3.1. Tweet Data

A total of 189,771 tweets were collected, including combinations of terms related to UVARs. The frequency of tweets across the period covered is presented in Fig. 1. The social media network's usage for discussing topics and issues related to UVARs increased throughout the study period.

Three periods of increased discussion can be observed in the figure: 2012, 2016, and 2020. A closer look at the monthly distribution in 2012 did not reveal a pronounced peak. The spike in tweet volume in 2016 corresponds to discussions in January (which started in the previous month) and April. A survey of the tweets collected during this period revealed that the period corresponds with the first and second phases of the odd-even scheme in Delhi, India, respectively. In May 2020, Twitter saw a significant increase in activity due to discussions surrounding the reintroduction of congestion charging in Central London, UK, which had been suspended as part of COVID-19 measures. Additionally, the city's integrated transport authority received a government bailout that included a fee increase from £11.50 to £15. Likewise, speculations on the expansion of the congestion charge were responsible for the spike in the number of tweets in October 2020.

All non-English tweets were filtered out from the data for the sentiment analysis, leaving 176,255 English tweets, representing about 93% of the initial data. The dominance of English tweets could be attributed to the fact that the search keywords contained only English terms identified from the literature. The collected data were cleaned by removing retweets and duplicates, as well as by other procedures in the preprocessing stage. An interesting observation made during preprocessing was that of the dominance of road pricing-related words in the dataset, as shown in Fig. 2. This observation was considered an indication of the possibility of general opinions about urban road pricing measures biasing the overall polarity of the collected data. Consequently, we disaggregated the data by conducting two parallel full archive retrieval processes from the Twitter API for keywords explicitly related to urban

road pricing in one set and other spatial interventions and access regulations in the last set. The three datasets were then subjected independently to sentiment analysis.

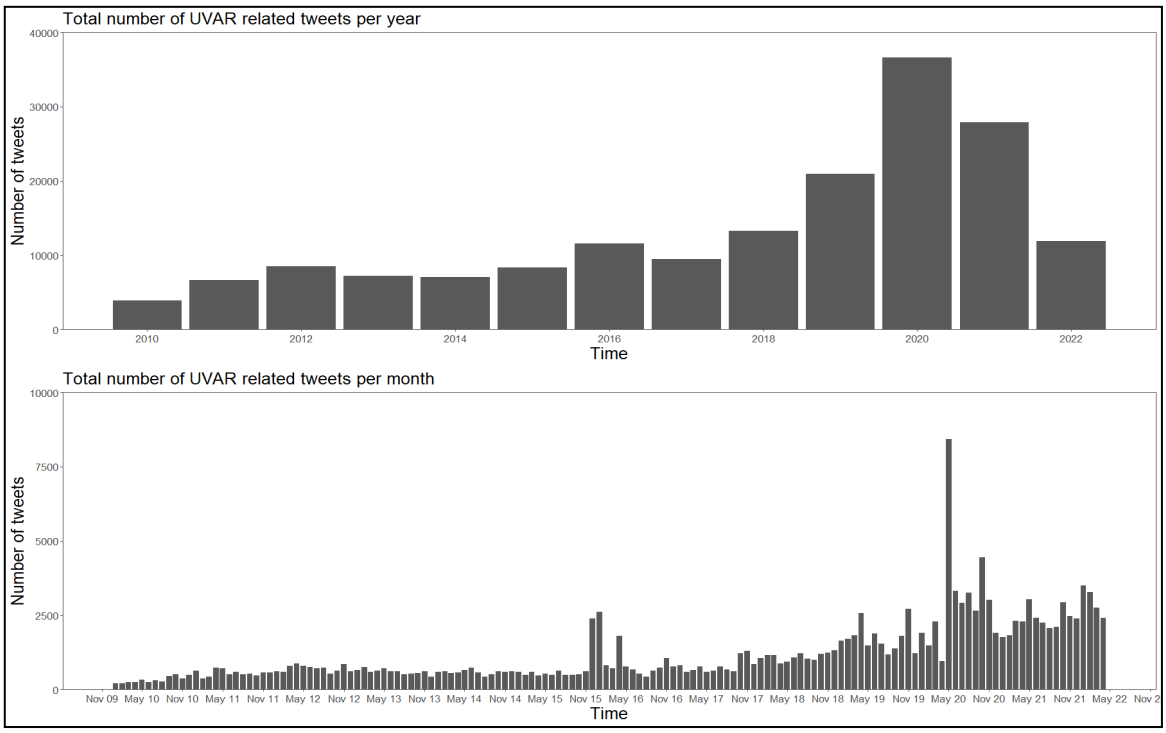

Fig. 1. Frequency distribution of total UVAR-related tweets retrieved

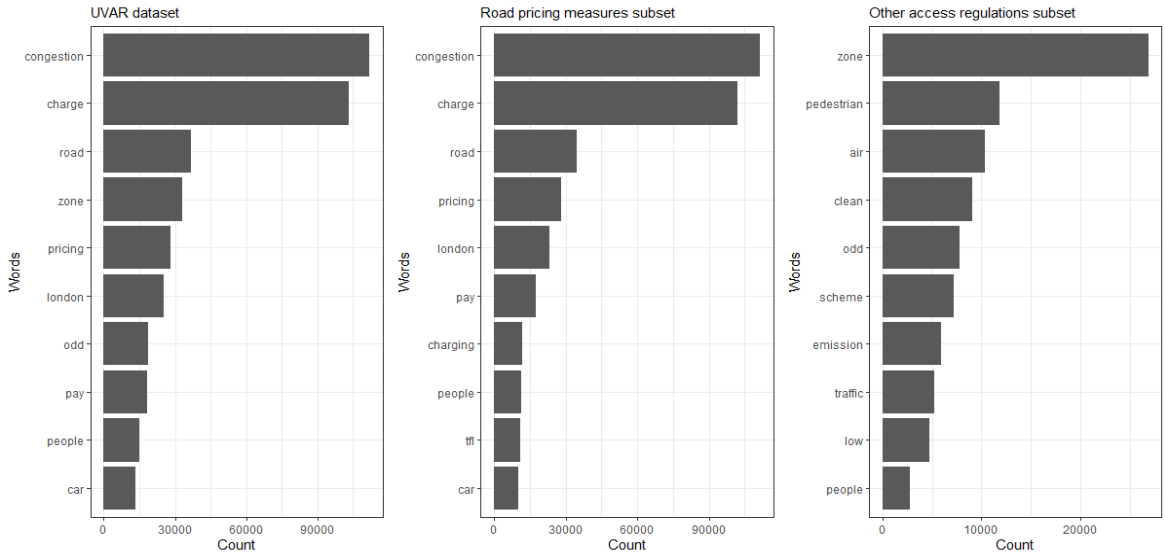

Fig. 2. Unique word frequency distribution

3.2. Sentiment Analysis

For the aggregated dataset, the sentiment analysis showed a mean score of 0.37, with about 45% of the tweets categorised as positive, 16% categorised as neutral, and 39% categorised as negative. Using the approach adopted by [12], tweets with a polarity score below -0.5 or above 0.5 were classified as strongly negative tweets and strongly positive tweets, respectively, as shown in Fig. 3. A high proportion

of the retrieved tweets were classified as neutral with a standardised sentiment score of zero. A sample of tweets, the corresponding score per word, and the compound score used as the baseline are presented in Tab. 1. A closer inspection of the data shows that the lexicon-based approach appropriately identified the polarity of most of the tweets (see the third row). Nevertheless, some field-specific words were unavailable in the dictionary. Therefore, some of the tweets that otherwise would have expressed polarised opinions were assigned a compound score of zero. While this could be deemed a demerit of the method, it should be considered a fail-safe approach. Similar observations were made for the road pricing-specific and the other general access regulations datasets.

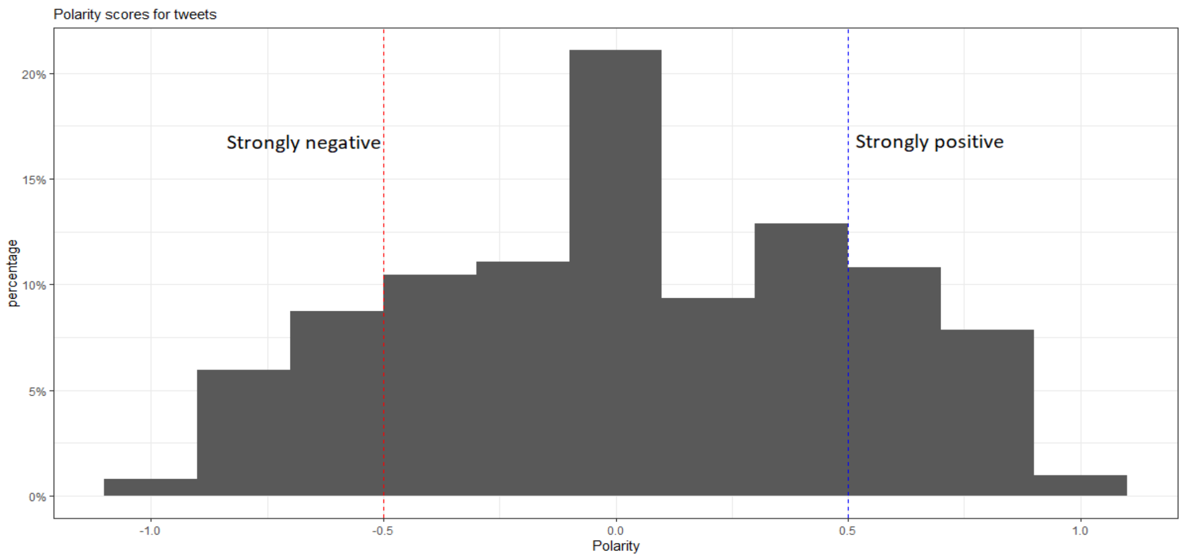

Fig. 3. Polarity scores for tweets including UVAR-related terms

Table 1

Sample of tweets and the associated word scores and sentiment scores

Sample Tweet	Word Score	Sentiment Score
"Bringing back the congestion charge in London. Stupid? Of course but politicians tend to be arrogant and stupid. Arrogant enough to think they can run the country and stupid enough to believe it. Arrogance is a form of stupidity."	{0, 0, 0, 0, 0, 0, 0, 0, -1.2, 0, 0, 0, 0, 0, 0, 0, -3.3, 0, -3.6, -3.3, 0, 0, 0, 0, 0, 0, 0, 0, 0, -3.6, 0, 0, 0, 0, -3.6, 0, 0, 0, 0, -2.85}	-0.984
"Congestion charge seems slyly mad"	{0, 0, 0, 0, -2.2}	-0.494
"Definitely and congestion charge ergh. I hate driving in London. Get yourself a bike :P"	{0, 1.7, 0, 0, 0, 0, 0, -2.7, 0, 0, 0, 0, 0, 0, 0, 1}	0
"Say this is about reducing congestion. There never was any congestion, they caused it. Charging at the train station? Really? How about you do a FOI request ?"	{0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, }	0
"Think that all schools should have a car free zone at least 1 mile around them, kids would benefit by walking the mile in clean air"	{0, 0, 0, 0, 0, 0, 0, 0, 0, 2.3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0, 0, 0, 0, 1.7, 0}	0.84
"I completely agree that a congestion charge should help and would hopefully improve air quality as well which is really needed! I just wish the bus service and cycle lanes would be improved as well."	{0, 0, 0, 1.793, 0, 0, 0, 0, 0, 1.7, 0, 0, 1.7, 1.9, 0, 0, 0, 1.1, 0, 0, 0, 0, 0, 0, 1.7, 0, 0, 0, 0, 0, 0, 0, 2.1, 0, 1.1}	0.961

The discussion will now turn to the evidence of changes in the public perception of different policy measures over the year. The monthly average of sentiments was plotted against time for the datasets. The outcome is presented in Fig. 4. As can be seen in the graphs, there has been a rise in the average public perception of UVAR measures across the covered period.

The mean monthly polarity of opinions expressed on Twitter was lowest in April 2016 during the second phase of Delhi's odd-even scheme. On the other hand, the polarity peaked in December 2020 when congestion charging was seasonally suspended.

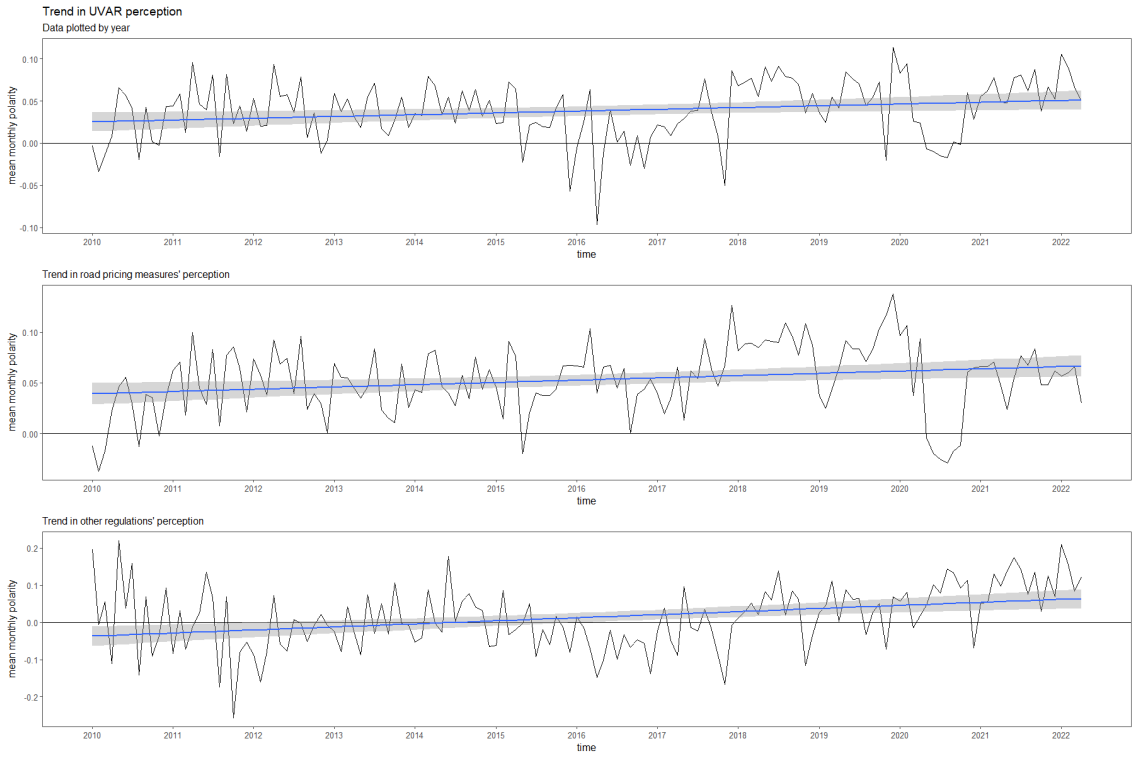

Fig. 4. Changes in average monthly polarity scores for UVAR-related tweets

However, the single most striking observation to emerge from the time-series data can be observed in comparing average public perception between the road pricing measures and other access regulation measures, with the former exhibiting a more positive overall perception than the latter. This result is counterintuitive, considering that pricing measures have been responsible for drastic spikes and dips in public perception, as evident in the aggregated data.

Considering the influence of the Delhi and London schemes on the overall trend, we attempted to analyse the data at these locations. There are two approaches for collecting tweet location-based data from the Twitter API. The first approach is to use the Twitter specialised place name or ID operator (set up at the granularity of neighbourhood, city, or country) to filter through the geotagged tweets in the search. The other approach is to use the geocoordinates (specifying a point radius or bounding box, both to a limit of 25 miles radius or length) in the search requests. However, it should be noted that location-based Twitter data searches often return few results, as only a small fraction of tweets are geotagged, as geotagging is an optional feature [22]. Inspecting the primary dataset, we observed that tweets referencing the schemes in both cities also originate from outside the cities, including the functional urban area and other neighbouring cities. The geocoordinate approach and filtering by the city name lead to the exclusion of these tweets. Consequently, we retrieved the data by using the country granularity level. The results of the analysis of the datasets made up of about 4,700 tweets and 700 tweets from the UK and India are presented in Fig. 5. Interestingly, the trend reveals that the perception of the UK schemes has remained fairly positive and improved only marginally over the years, while the

average perception in India declined. However, the sparsity of geotagged tweets for the geographical-based analysis makes it difficult to draw direct inferences from the data.

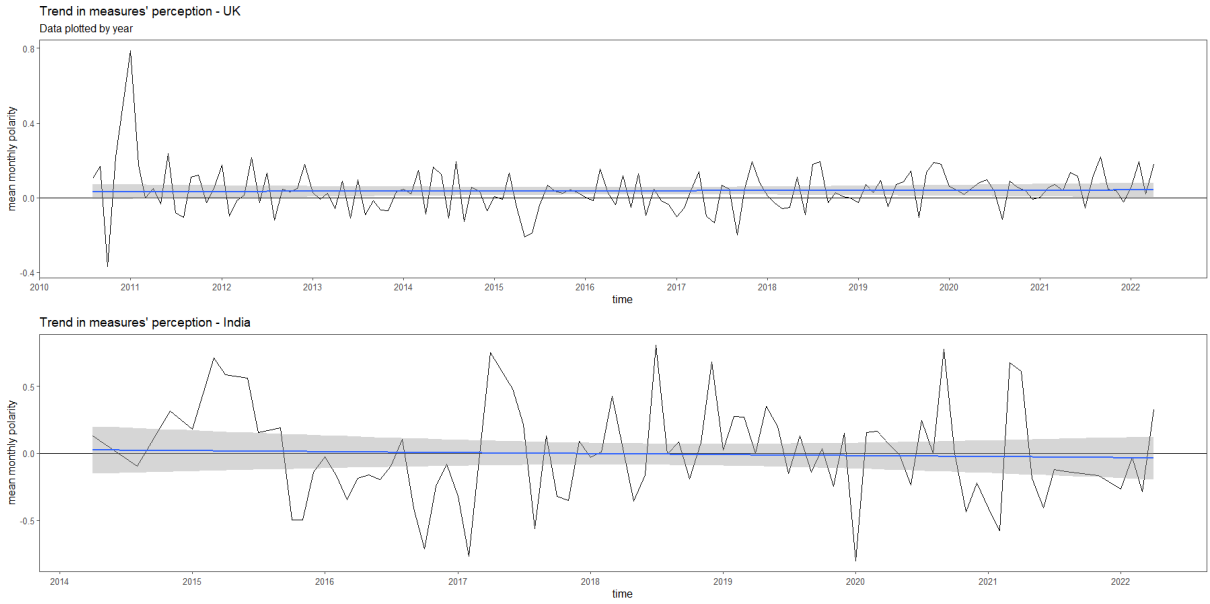

Fig. 5. Changes in average monthly polarity scores for geotagged UVAR tweets in the UK and India

3.3. Topic Modelling

Topic modelling using LDA with the Gibbs sampling technique was conducted on the document term matrix created from the tweet text corpus and reduced sparsity to 0.99 separately for the strongly positive and negative data. Four clusters were modelled for each sentiment pole, and the identified keywords (and their respective levels of relative importance) are presented in Fig. 6 and Fig. 7.

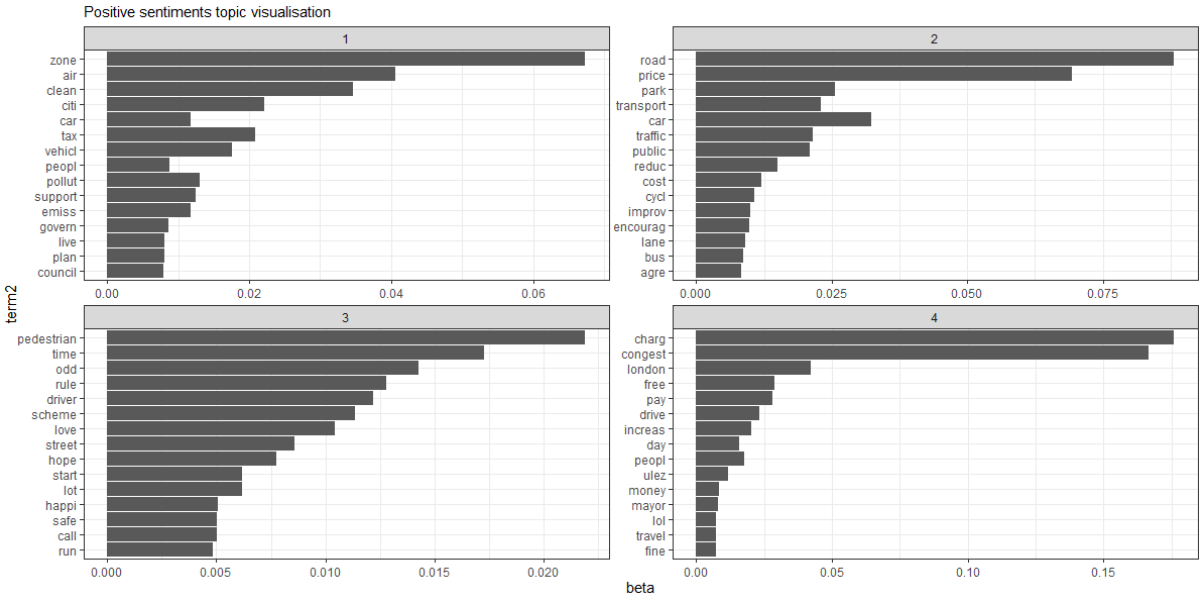

Fig. 6. Quantitative topic clustering for tweets with strongly positive sentiments

By inspecting the positive tweets clusters, Topic 1 can be attributed to tweets declaring support for plans to reduce emissions by implementing low emission zones or clean air zones. Topic 2 relates to

tweets describing how road pricing measures can reduce car traffic flow in cities, encourage cycling, and provide revenue for public transport improvements. Topic 3 contains keywords that describe how few car-dependent cities and pedestrianised areas bring about safety on urban streets. At the same time, the final cluster can be attributed to tweets exhibiting positive sentiments during periods when UVAR measures were suspended in London.

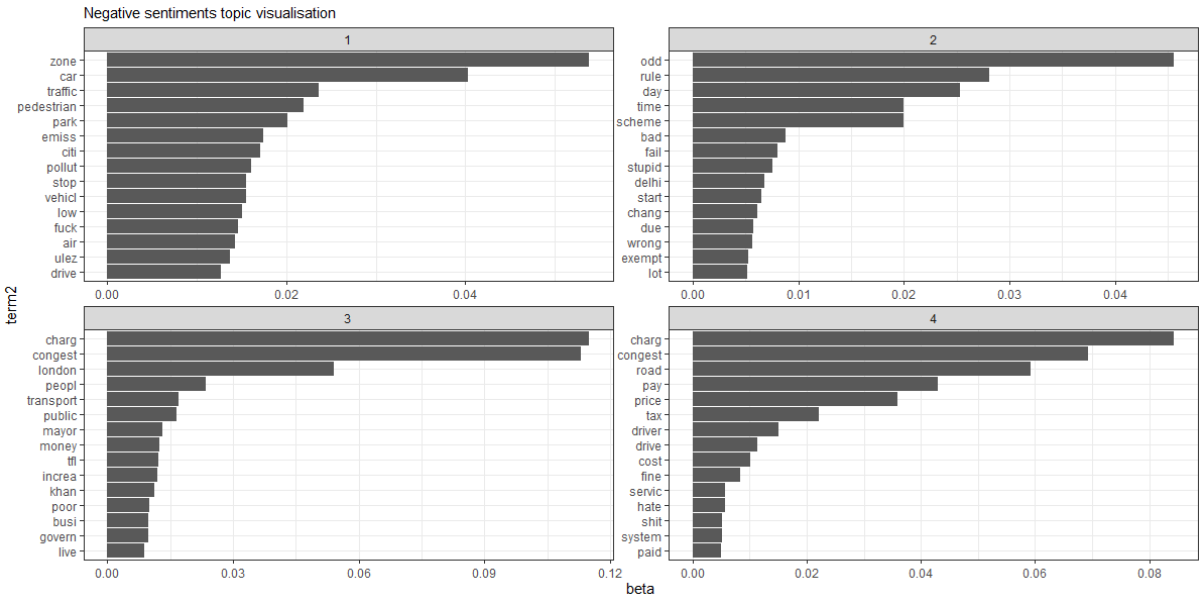

Fig. 7. Quantitative topic clustering for tweets with strongly negative sentiments

Topics emerging from the negative sentiment clusters include different displeasures expressed about ultra-low emission zones in Topic 1 and the Delhi odd-even rule with exemptions in Topic 2. The third topic cluster contains keywords indicating tweets channelled to London's integrated transport authority and the city's mayor. The last topic cluster shows public disapproval of the congestion charge as an additional road tax for drivers.

4. DISCUSSION

This study aimed to explore the public discussion on UVARs to elicit people's perceptions of these measures, drivers, barriers, enablers, setbacks, the ways in which the public perception of UVARs has morphed over time, and the events and stimuli responsible for these changes. The results show that UVAR is a very prominent topic in public discussions based on the volume of tweets retrieved containing keywords related to the various interventions used in different cities worldwide. Although the tweets varied primarily based on context and the information they contained, as conveyed in the results, the insights portray a departure from the general notion of UVARs, as the average polarity of the tweets tends to be more on the positive side of the sentiment spectrum than on the negative side. This finding is significant, as low social acceptability has been a major barrier to adopting and implementing UVAR measures in many cities, as identified by several scholars [4, 23–26]. Fig. 4 shows changes in average polarity observed over time. Despite the different oscillations, a relative increase in the sentiment scores can be observed for the 12 years covered by this study. Interestingly, the sharp dips and spikes seen in the portrayed results could be explained by changes in policies and events, thus confirming that the results accurately reflect societal occurrences.

Concerns about equity and accessibility, the availability of alternative mobility measures, the cost of the congestion charge, business needs, definitions of exemptions, and revenue-related issues are the central themes that explain the bulk of the strongly negative tweets identified from the topic modelling results. These themes generally encompass the factors responsible for the low public acceptability of UVAR measures. While these themes have been established in previous studies using different

approaches [27–29], the common finding lends further credence to the methodological approach undertaken in this study. The concerns emerging from different geographical locations at various times across the study period reiterate that despite the differences in the components of the various policy measures to drive a shift in behaviour from the absolute dependence on passenger car travel to sustainable modes, policy acceptance and positive perception often include similar components. These components have been established through different good practice cases across implementing cities, including tailored consultation, transparency, effective communication, the recognition of citizens as major stakeholders, and the bundling of UVAR measures with supporting mobility measures.

The range of words found in tweets expressing positive sentiments about the measures evidences the gains experienced in areas where people have been prioritised over the access of cars. Many of the tweets have become instruments of knowledge transfer and advocacy across the social network platform. Many users refer to successful implementation elsewhere and wish for the same in their cities. This subtle advocacy for alternative mobility narratives in cities, which have proven successful in other transport-related use cases (e.g., protected bike lanes, public transport improvements), can also become pivotal to the acceptance of measures regulating the access of passenger cars in urban areas. Therefore, improved perceptions will translate into a reduction in the political difficulty of implementing UVARs and help introduce stick measures into the existing carrot measures, which are often easier to implement. This will create the right mix of push and pull measures needed for effective transport decarbonisation and climate change mitigation.

However, the study's most interesting finding is that road pricing measures, such as the congestion charge, are subjects of more positive tweets than other regulatory measures. Due to their low public acceptability, road pricing measures are among Europe's least-implemented UVAR measures (see [30]). The existence of many studies [4, 23–25, 31–32] investigating the system design and implementation barriers further attests to this matter when compared to the availability of literature discussing other UVAR measures. Pricing measures are expected to have a more negative perception. A plausible explanation for this somewhat unexpected finding could be the supposed ease of paying to access tolled areas compared to the perceived cost of making a modal shift to more sustainable mobility options or replacing polluting vehicles with environmentally friendly vehicles. Further research is needed to verify this finding.

In general, the present study has found that there has been a general improvement in the public perception of UVARs due to their potential to bring massive gains within both short-term and long-term horizons at a low cost. The study also provides empirical evidence supporting the theory that the public perception of UVAR measures has decreased towards implementation and remarkable improvement [23]. The study has also demonstrated the utility of social media forums as measures for assessing the experience and opinions of the public on policy and measure planning for sustainable urban mobility. However, the present work also has some limitations. Twitter and other social media users usually belong to the younger, educated, and urban subset of the population, and their opinions may not entirely represent general public perceptions [33]. Therefore, general population research using social media analysis should be triangulated with other approaches to address this shortcoming. Although the study used the VADER lexicon and rule-based sentiment analysis tool, which is specifically attuned to sentiments expressed in social media [18], the language limitation and the non-availability of some common words used in transport-related discussions call for the development of multilingual dictionaries with broader lexicons. Furthermore, social media trolling and bot accounts could have influenced the outcomes. Therefore, future research following the same approach used in the present study will require more filtering conditions in the data preprocessing stages.

5. CONCLUSION

This study explored how the public perception of topics and issues related to UVARs can be extracted from Twitter and classified based on their sentiments through natural language processing methods. Patterns observed in the extracted data and the topics modelled from a cluster of words generated are consistent with events and talking points characterising UVAR discussions in society. However, an

unexpected finding of the study is that one of the least publicly acceptable UVAR measures, road pricing, is perceived more positively than other UVAR measures that have been successfully implemented. While the discussion offered an alternative explanation for this observation, verifying this finding will be the subject of further research using a more sophisticated transport policy-specific approach. This study indicates that citizens use social media to convey their opinions, relate their mobility needs, and inform others about their overall experiences. This shows that data from social media can provide key inputs detailing mobility needs and indicating public perceptions of the decision-making process and mobility management actions needed to plan and sustain measures for sustainable urban development. In addition, the subtle advocacy observed in the modelled topics across the positive tweets positions social media as a feasible tool for shaping and influencing public opinion. Therefore, social media is pivotal for urban authorities' policy information and communication activities.

This study recognises that the optionality of geo-identification on social media might be a limitation for adopting social media data analysis as a policy tool. However, when location-based keywords and language models are used, social network analysis, in combination with additional data sources, can help to overcome the challenge of determining users' locations without compromising their privacy. Finally, while this study used historical data to analyse public perception, further research could use an almost real-time filtered stream of data to develop a transport measures dashboard for monitoring sustainable urban mobility measures. These improvements and potentials will be explored for a specific use case as a future development.

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